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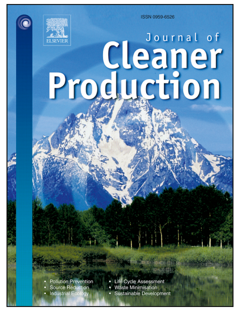
Digital Object Identifier (DOI):
10.1016/j.jclepro.2020.123848

Journal Pre-proof



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PII: S0959-6526(20)33893-2

DOI: https://doi.org/10.1016/j.jclepro.2020.123848

Reference: JCLP 123848

To appear in: *Journal of Cleaner Production*

Received Date: 18 May 2020

Revised Date: 11 August 2020

Accepted Date: 17 August 2020

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Coupling coordination between carbon emissions and the eco-environment in China

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Abstract: Understanding the coupling mechanisms between carbon emissions and the eco-environment is essential for building sustainable economies. Based on the coupling coordination model, this paper investigates the coordination degree of carbon emissions and the eco-environment in China from 2009 to 2015. The Logarithmic Mean Divisia Index decomposition method was used to identify the key factors affecting the coordination degree. Furthermore, different scenarios were simulated to show the impact of changes in government priorities on the coordination degree. The results show that the dynamic relationship between carbon emissions and the eco-environment in China has reached a barely balanced stage, but a few provinces are still struggling with imbalances. The coordination level of carbon emissions and the eco-environment becomes the key factor affecting coordinated development, while the interaction intensity has a limited effect. Further analysis indicated that although the carbon emission evaluation value has a positive effect on promoting an increase in the coordination degree, the eco-environment evaluation value determines the trend of coordinated regional development. Moreover, the priorities of government policymakers have a substantial impact on coordinated development, but these impacts gradually diminish as the differences in evaluation

values decrease. These findings contribute to the formulation of effective regional sustainable development strategies.

Keywords: China; Carbon emissions; Eco-environment; Coupling Coordination Model; LMDI

1. Introduction

Since 2006, China has been the world's largest carbon emitter (Boden et al., 2013; Liu et al., 2016); By 2015, carbon emissions accounted for about 28.2% of the global total (BP, 2016). China is taking an active part in building capacity to control greenhouse gas emissions and adapt to climate change (Liu et al., 2017; Lu et al., 2017). At the 2015 United Nations Climate Change Conference in Paris, China promised to achieve the national intended contribution target of carbon emission reductions by 2030, where carbon emissions were predicted to peak around 2030, while China strives to reach this peak as soon as possible (Jiang et al., 2017; Meng et al., 2018). However, economic growth is strongly dependent on energy consumption (Bhattacharya et al., 2015; Schandl et al., 2016), the established peaking target and emission reduction trend are very uncertain, and it is predicted that carbon emissions will still increase in the future (Lin et al., 2018). However, a fact that cannot be ignored is that anthropogenic greenhouse gas emissions, represented by fossil energy combustion, have become the main cause of environmental change (Busch and Hoffmann, 2011; Nejat et al., 2015; De Stefano et al., 2016). In addition, due to global warming, the increase of extreme weather and the continuous expansion of human activities, deforestation, grassland degradation, desertification, soil erosion, and other problems are becoming more and more serious (Liu et al., 2019), which have caused an accelerated depletion of non-renewable natural resources and the continuous deterioration of the eco-environment (Escobar and Vredenburg, 2011). Under such circumstances, the importance, complexity, and challenges of managing the natural environment will continue to increase (Tate and Bals, 2018; Jonek-Kowalska, 2019). Coordination is one of the basic principles of sustainable development, where the core connotation lies in the emphasis on the sustainable and coordinated development of the economy, society, and eco-environment in the process of economic development. Therefore, it is necessary to correctly grasp the coordination relationship between carbon emissions and the eco-environment to provide a reference for policymakers to promote high-quality sustainable development.

Coupling theory is one of the methods that are widely used in existing studies to study the coordination relationship between systems in the process of sustainable development (Kunz et al., 2013). "Coupling" is a phenomenon originating in the physical sciences and used to describe the interaction of two or more systems (Zhou et al., 2017; Song et al., 2018). The research based on this theory has been embodied in many fields. For example, Srinivasan et al. (2013) investigated the relationship between urbanization and water resources. Zhou et al. (2017) focused on the relationship between production, life, and ecology of regional urban agglomerations. Fan et al. (2019) evaluated the coordinated development trend of the urban social economy and eco-environment. Li et al. (2012), He et al. (2017), and Liu et al. (2018) analyzed the relationship between urbanization and the eco-environment. Shen et al. (2018) discussed the coordination between the social economy and carbon emissions. Song et al. (2018) focused on the relationship between carbon emissions and urbanization. As mentioned above, coupling theory has been widely studied in the fields of carbon emissions and the eco-environment, which, however, are independent of each other. No research has considered both of these fields simultaneously. Moreover, previous research was mostly limited to local areas. Although more micro information can be obtained, the relationship between China's macro-level carbon emissions and the eco-environment has not been clarified to date. In addition, although a coupling coordination model can measure the coordination degree between systems, existing research did not take the contribution of each subsystem to the coordination degree into account.

In recent years, the development of the logarithmic mean Divisia index (LMDI) has provided a new way to identify the key factors in the coordination between carbon emissions and the eco-environment. The advantages of the LMDI lie in the use of general time-series data, the relatively low data requirements, simple structure, easy operation, and convenience for retrospective or prospective analysis. Therefore, the LMDI is widely used to explore the driving factors of energy consumption, energy-related emissions, and environmental change (Wang et al., 2017; Chen et al., 2018a; Tan et al., 2018; Cheng et al., 2019). For example, Jeong and Kim (2013) decomposed greenhouse gas emissions from industrial manufacturing in South Korea. Marcucci and Fragkos (2015) explored short- and long-term drivers of alternative decarbonization paths in China, India, Europe, and the United States. Branger and

Quirion (2015) examined changes in carbon emissions from the cement industry in Europe. Chen et al. (2018b) explored the impact of carbon dioxide emission intensity from fossil energy in OECD countries. Xie et al. (2019) discussed the driving factors of carbon emissions in China's power industry. Chong et al. (2019) analyzed the drivers for the growth of energy-related carbon emissions in Malaysia. Zhang et al. (2019) identified the key influencing factors of $PM_{2.5}$ concentrations in 152 cities in eastern, central, and western China. In addition, the method was also used to discuss water resources (Zou et al., 2018), electric power (Cheng et al., 2019), and sustainable energy (Chen et al., 2019). Although the scope of the LMDI is relatively limited (Chen et al., 2018c), it has good mathematical properties and can be easily combined with other theories to analyze specific problems (Chen et al., 2018d).

Therefore, the purpose of this study is to examine the relationship between China's carbon emissions and the eco-environment, to further identify key factors influencing this relationship, and to discuss the impact of policymakers' changing priorities on the degree of coordination. Compared with existing studies, the marginal contributions of this study are as follows: 1) Carbon emissions and the eco-environment are integrated into a comprehensive analytical framework to test the coordination degree between them. Balancing carbon emissions and the dynamics of the eco-environment is an important lever for implementing the concept of a green and coordinated development advocated by China, which provides strong evidence for whether economic growth has kept pace with environmental protection. 2) In this study, the research methods are expanded, i.e., the coupling coordination model is combined with the LMDI method, and the key factors affecting the coordination degree are identified from the mechanisms and components. This is a beneficial attempt to accurately grasp the trends in the coordination degree changes and the internal mechanisms of influence. At the same time, this method can be applied to a wide range of similar studies. 3) This study further simulates the role of changes in government priority with respect to the coordination of carbon emission and eco-environment under different scenarios by adjusting the parameters of the coupling coordination model.

The remainder of this paper is arranged as follows. The second section introduces the research methods, data, and sources, including the coupling coordination model and LMDI decomposition method. The third section presents the results and discussion, which describes the changes and distribution in carbon emissions and vegetation carbon sequestration, the coordination degree and decomposition results of carbon emissions and the eco-environment as well as the variation trend in the coordination degree under different scenarios. The fourth section presents the main conclusions and provides policy implications.

2. Methods and data

2.1 Coupling coordination degree model

To evaluate the coordination between carbon emissions and the eco-environment, this paper establishes an evaluation system. Within the evaluation system, two coupled subsystems were defined via respective indicators. The carbon emission subsystem consists of 16 indicators from four areas that are considered to influence carbon emissions: economy, population, energy, and anthropogenic land use. In the context of this subsystem, all carbon emissions refer to carbon dioxide generated by fossil fuel consumption. The impacts of these indicators on carbon emissions have been documented by previous research (Zhang and Tan 2016; Ibrahim and Joseph, 2017; Xie et al., 2018; Wang and Jiang, 2019). During the process of economic development, the carbon emission subsystem becomes increasingly complex by integrating a growing number of influencing factors. In addition to the scale effect, interactions between the influencing factors become increasingly important. The eco-environment subsystem consists of 10 indicators from four areas, including net primary productivity (NPP), vegetated land cover, forest area, and government environmental expenditure. In this context, eco-environment refers to the quantity and quality of water, land, biological, and climatic resources that support human livelihoods and development. This study focuses on terrestrial ecosystems, including forests, thickets, meadows, wetlands, and grasslands. Changes in the eco-environment subsystem reflect the shift from a relatively static state to a dynamic state, which is accelerated by anthropogenic activities. NPP, in particular, is one of the most important indicators in measuring eco-environmental processes (Field et al., 1998; Zhao and Running, 2010). The amount and spatial distribution of NPP directly affect the functioning of the terrestrial carbon sink. NPP, in turn, is directly related to the total area of vegetated land, the area of vegetated land per capita, and the proportion of vegetated land, which are all constantly changing due to human activities (Erik et al., 2016). Forest cover represents one of the most important components of the eco-environment, as forests act as a major terrestrial carbon sink (Pan et al., 2011; Sun et al., 2019). Total forest area, forest area per capita, and percentage of forest cover were used as measures for forest resources. The proportion of government environmental expenditure, with total fiscal expenditure, was used to measure environmental protection.

[Insert Table 1 here.]

The entropy method was used to calculate the weight of the indicator. The indicators were weighted according to their variability, which reduced the interference of subjective selection factors. The process was as follows.

The range method was used to standardize the index. (Eq. 1):

$$y'_{ij} = \frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} \tag{1a}$$

$$y'_{ij} = \frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})} \tag{1b}$$

Where i and j are provinces and indicators, respectively. y_{ij} represents the actual value of the indicator, and y'_{ij} represents the standardized value. When the indicator was positive, equation (1a) was applied, and when the indicator was negative, equation (1b) was applied. In both cases, a high absolute value indicates a high importance of a given indicator within the studied system.

The weight of each indicator was determined based on information entropy (Eq. 2):

$$e_j = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij}$$

$$w_i = \frac{1 - e_i}{k - e_i} \tag{2}$$

Where e represents the information entropy for each indicator, n is the number of samples, k is the number of indicators, and w refers to the indicator weight. $p_{ij} = y'_{ij} \Big/ \sum_{i}^{n} y'_{ij}$, represents the proportion of the indicator, if $p_{ij} = 0$, it is defined as $\lim_{p_{ij} \to 0} p_{ij} \ln p_{ij} = 0$. Appendix A contains the specific weight results for all indicators.

The standardized values and weights were used to calculate the evaluation value of the subsystem (Eq. 3):

$$U = \sum_{j=1}^{k} w_i \times y_{ij}^{'} \tag{3}$$

where U represents the evaluation value of each subsystem, in this case, the carbon emission evaluation value (CEV) and the eco-environment evaluation value (EEV).

Through the above steps, the coupled coordination model of carbon emissions and the eco-environment was established as follows:

$$D_i = \sqrt{C_i \times T_i} \tag{4}$$

$$C_i = \left\{ \frac{CEV \times EEV}{\left[\left(CEV + EEV \right) / 2 \right]^2} \right\}^{1/2} \tag{4a}$$

$$T_i = \alpha \times CEV + \beta \times EEV \tag{4b}$$

where D represents the coupling coordination degree between carbon emissions and the eco-environment, which is between 0 and 1. A low value indicates that the subsystems are unbalanced and have detrimental effects on each other, and a high value indicates that the subsystems are coordinated and achieve a relative sustainable development. C represents the coupling degree, indicating the interaction intensity. T represents the comprehensive evaluation value, indicating the coordination level. α and β are contribution coefficients. We assumed that the evaluated subsystems have equal status, considering that China's carbon emission reduction and environmental protection are equally important to social development. Therefore, $\alpha = \beta = 1/2$.

2.2 Decomposition method

This study used the LMDI to further determine the key factors of the coordination degree between carbon emissions and the eco-environment. Ang (2004; 2015) showed that the LMDI is one of the most ideal decomposition methods, which not only has many advantages, such as a good theoretical foundation, wide applicability, practicability, and easy interpretation of results (Ang, 2004; 2015) but also overcomes the problem of zero and negative values in the decomposition process (Ang, 2007a; 2007b). It avoids the limitation of arithmetic mean divisia index decompositions and realizes complete decomposition.

The interaction intensity and coordination level between carbon emissions and the eco-environment can be decomposed as follows.

$$D_i = \sqrt{C \times T} = \sqrt{C} \times \sqrt{D}$$

$$D_i = C^* \times T^* \tag{5}$$

According to the LMDI method:

$$\Delta D = D^t - D^0 = \Delta D_{C^*} + \Delta D_{T^*} \tag{6}$$

The detailed derivation of the decomposition process can be found in Ang and Liu (2011). The decomposition itself was performed as follows:

$$\begin{aligned} \Delta D_{C^*} &= \sum_i L(D_i^t, D_i^0) \ln\left(\frac{C_i^{*,t}}{C_i^{*,0}}\right) \\ \Delta D_{T^*} &= \sum_i L(D_i^t, D_i^0) \ln\left(\frac{T_i^{*,t}}{T_i^{*,0}}\right) \end{aligned} \tag{7}$$

where t is the reporting period and 0 is the base period. $L(D_i^t, D_i^0) = \frac{D_i^t - D_i^0}{\ln D_i^t - \ln D_i^0}$ is the logarithmic average weight function. ΔD_{C^*} and ΔD_{T^*} represent the effect of the coupling degree and comprehensive evaluation value on the coordination degree, respectively.

However, the key in determining the level of coordination is the evaluation value of each subsystem. Therefore, it is necessary to decompose the effects of these values. To achieve this, Eq. (4) had to be converted to Eq. (8), as follows.

$$D_i = \sqrt{\left\{\frac{CEV \times EEV}{[CEV + EEV/2]^2}\right\}^{1/2} \times \left[(CEV + EEV)/2\right]}$$

$$D_i = (CEV)^{1/4} \times (EEV)^{1/4}$$

$$D_i = CEV^{'} \times EEV^{'} \tag{8}$$

Thus, the following equations could be derived, based on the LMDI method (Eq. 9, 10):

$$\Delta D = D^t - D^0 = \Delta D_{CEV^{'}} + \Delta D_{EEV^{'}} \tag{9}$$

$$\begin{aligned} \Delta D_{CEV^{'}} &= \sum_i L(D_i^t, D_i^0) \ln\left(\frac{CEV_i^{',t}}{CEV_i^{',0}}\right) \\ \Delta D_{EEV^{'}} &= \sum_i L(D_i^t, D_i^0) \ln\left(\frac{EEV_i^{',t}}{EEV_i^{',0}}\right) \end{aligned} \tag{10}$$

where $\Delta D_{CEV^{'}}$ and $\Delta D_{EEV^{'}}$ represent the effect of the carbon emission evaluation value and the eco-environment evaluation value on the coordination degree, respectively.

2.3 Data

This study used data from 30 provinces in China. Tibet, Hong Kong, Macau, and Taiwan were excluded because some indicator data were missing. The energy consumption, GDP, fiscal expenditure, environmental expenditure, and population data used in this study were taken from the *China Energy Statistics Yearbook* (CESY, 2016) and the *China Statistics Yearbook* (CSY, 2016), respectively. To eliminate the effects of inflation, the nominal GDP was adjusted to 2010 constant prices, according to the GDP index given in the *China Statistics Yearbook*. Carbon emissions data from fossil fuel sources were derived from the *China Emission Accounts and Datasets* (CEADs, 2015*)*. Anthropogenic land-use and vegetated land cover areas were taken from a land-use survey provided by the Ministry of Natural Resources of the People's Republic of China (LUS, 2016). To ensure data consistency, this study selected data for the period from 2009 to 2015. NPP data were derived from a MODIS-MOD17 product, provided at a resolution of 30 arc seconds (approximately 1 km) (Running and Zhao, 2015) using the improved Carnegie-Ames-Stanford Approach model (Field et al., 1995). For NPP estimates, it was assumed that one unit of dry plant matter can absorb 1.63 units of carbon dioxide (Xu et al., 2018), and plant matter contains 45% carbon. Based on these assumptions, the total carbon sequestered in the vegetation in each province was calculated.

3. Results and discussion

3.1 Trend and distribution of carbon emissions and vegetation carbon sequestration

Figure 1 shows the changing trend of carbon emissions and vegetation carbon sequestration in China from 2009 to 2015. Carbon emissions rose from 7656 million tons in 2009 to 9557 million tons in 2015 (an increase of 20%) but the growth rate gradually slowed down after 2012. However, the variation in vegetation carbon sequestration was relatively stable, and the maximum amplitude was 10% during the study period. Although China's vegetation carbon sequestration is higher than its carbon emissions, it is unbalanced in that only 5% of the world's vegetation carbon sequestration needs to absorb 28% of the world's carbon emissions.

[Insert Fig. 1 here.]

Figure 2 shows the distribution of carbon emissions and vegetation carbon sequestration in Chinese provinces in 2009 and 2015. Except for Beijing and Yunnan, where carbon emissions fell slightly due to a decline in energy consumption, especially coal consumption (CESY, 2016), the other provinces experienced a relatively obvious rise, especially Shandong, Hebei, Jiangsu, Inner Mongolia, and Xinjiang, with growth rates exceeding 100 million tons. However, there was no significant change in vegetation carbon sequestration. Hot spots were still concentrated in Yunnan, Sichuan, Inner Mongolia, and Heilongjiang, where vegetation coverage was relatively high. Although the distribution characteristics of carbon emissions and vegetation carbon sequestration in China have not undergone great changes, they can reflect the increasing pressure of carbon emissions on the eco-environment.

[Insert Fig. 2 here.]

The results also revealed that the increase in carbon emissions was much larger than the change in vegetation carbon sequestration, and there were obvious regional differences. The direct cause of the increase in carbon emissions is the increase in the consumption of fossil fuels (Imran et al., 2019), and the underlying mechanism is the combined effect of economic development, population size, urbanization, and land-use pattern change. The variation range of vegetation carbon sequestration was small, and there was an obvious spatial difference. Given China's vast size, the natural environment, and topography vary from province to province. Although land-use changes, such as urbanization and deforestation as well as seasonal vegetation dynamics, may affect regional carbon sinks (Xu et al., 2018), the government has paid more attention to environmental protection in recent years, and measures such as afforestation and conversion of farmland to forests have greatly increased the carbon sequestration potential.

3.2 Coordinated trend of carbon emissions and the eco-environment

As shown in Figure 3, the coordination degree between carbon emissions and the eco-environment in China showed a slight upward trend, with the average value reaching 0.53. This indicates that the coupling between carbon emissions and the eco-environment has reached a barely balanced stage. Although the coordination degree is low at present, it can be expected that with the advancement in the economic and social development, the coordination degree will further improve. Due to the regional differences in economic development and environmental quality, the dynamics of the coordination degree varied in different provinces. The coordination degree of most provinces only changed slightly, but Beijing, Tianjin, Hebei, and Inner Mongolia showed a significant upward trend, whereas Shanghai, Hainan, and Xinjiang showed a slight decline. Generally, the coordination degree of most provinces was between 0.5 and 0.6. Inner Mongolia, Heilongjiang, Guangdong, Sichuan, and Yunnan all scored higher than 0.6, largely due to the higher environmental quality of these provinces. On the contrary, there were still some provinces in a slightly unbalanced phase, which maintained a downward trend. These results further confirm that although China has achieved basic coordination between carbon emissions and the eco-environment, there are large regional differences, and the imbalances in some provinces are still pronounced.

[Insert Fig. 3 here.]

Figure 4 shows the spatial distribution of carbon emission evaluation and eco-environment evaluation values (mean values). The carbon emission evaluation value gradually decreased from east to west. Except for Qinghai, Inner Mongolia, and Heilongjiang, the eco-environmental evaluation value showed a decreasing trend from south to north. Moreover, the eco-environment evaluation value in the provinces with a higher coordination degree was also higher. Provinces with slight imbalances were usually characterized by a low eco-environment evaluation value or both low carbon emission and eco-environment evaluation values, e.g., Tianjin and Shanghai, where the eco-environment is severely burdened by factors, such as a small land area, rapid economic development, accelerated urbanization, and increased artificial land use (Liu et al., 2018). Similarly, Gansu, Ningxia, Henan, Shanxi, and Hainan have low forest coverage, low vegetation carbon sequestration capacity, and a relatively fragile eco-environment (Song et al., 2018). These results show that carbon emissions and eco-environment have an obvious spatial pattern, and the optimization of eco-environment will ameliorate the coordinated development process.

[Insert Fig. 4 here.]

The spatial distribution of the carbon emission evaluation value was closely related to the east-west gradient formed by the economic development (Zhang et al., 2018), while the spatial distribution of the eco-environment evaluation value was more in line with the north-south difference formed by the natural environment.

Although the two are barely balanced, low coordination will continue to prevail in China in the long-term. Therefore, to improve the coordination level of carbon emissions and the eco-environment, it is necessary to consider not only the changes in the respective carbon emission and eco-environment evaluation values, but the changes in the influencing mechanisms. Meanwhile, due to the existence of regional differences, the coordination degree of carbon emissions and the eco-environment is not uniform across the country; some regions are facing an imbalance crisis, and the government needs to adjust their policy to achieve sustainable coordinated development.

3.3 Decomposition results

The LMDI method was effectively combined with the coupling coordination model to identify the key factors influencing the coordination degree of carbon emissions and the eco-environment with respect to mechanisms and composition, respectively. Figure 5 shows the key factors of the coordination degree between carbon emissions and the eco-environment from a mechanistic perspective. The effect of the coupling degree was only prominent in some areas. For example, the change in the coupling degree resulted in an increase in the coordination degree of Beijing by 0.032, accounting for 55% of the coordination degree, followed by Tianjin (0.011), Hebei (0.006), and Inner Mongolia (0.008). On the whole, the interaction intensity between carbon emissions and the eco-environment had a weak influence on the coordination degree. In other words, the interaction between carbon emissions and the eco-environment is not detectable in the short term but maybe more important indirectly or in the long term. By contrast, the effect of the comprehensive evaluation value exceeded the coupling degree in most provinces, such as Tianjin (0.025), Hebei (0.016), and Chongqing (0.021). The decomposition results also showed that the increase in the comprehensive evaluation value of about 2/3 of the provinces promoted an increase in the coordination degree. This indicates that the coordination level between carbon emissions and the eco-environment is a key factor affecting the coordination degree. These observations are consistent with China's current stage of development. In the early stage of development, an excessive economic growth at the expense of the environment led to a low level of coordination between carbon emissions and the eco-environment (Cialani, 2007; Lee and Min, 2015). Fortunately, with increasing wealth and education, the government and societies have come to realize the importance of sustainable growth. The increasing commitment of the government is further reflected in the efforts to strengthen national environmental regulations, which effectively improved the coordination level (Chan, 2015).

[Insert Fig. 5 here.]

Figure 6 discusses the key factors of the coordination degree of carbon emissions and the eco-environment from the composition perspective. The rise in the carbon emission evaluation value had different positive impacts on the coordination among various provinces, where only Qinghai and Xinjiang experienced a restrained effect. This is attributed to the implementation of low-carbon policies in recent years, which has promoted the innovation of production technology, optimized the industrial structure, and improved carbon emission efficiency. To a certain extent, the increase in carbon emissions has been restrained and the quality of the economic development improved, and the effects differed based on regional development differences (Guo et al., 2018; Wang et al., 2019). By contrast, the eco-environment evaluation value had a strong positive effect only in the Beijing–Tianjin–Hebei region. This is mainly because the region has actively promoted industrial relocation, attached great importance to pollution reduction and environmental protection, strictly regulated high-polluting industries, and significantly improved the eco-environmental quality. However, in more than half of China's provinces, the eco-environment evaluation value had an inhibitory effect on the coordination degree, directly changing the development trend of the coordination degree, especially in areas where the carbon emission evaluation value increased only slightly. This indicates that China's economic growth is built on a massive input of energy, a continuous increase in population, and rapid urbanization, which leads to the accelerated depletion of natural resources and a continuous decline in vegetation and forest coverage (Chan, 2015). Another implication is that the negative impact of eco-environmental degradation will be further amplified in areas where carbon emission control is inadequate.

[Insert Fig. 6 here.]

Two things can be inferred from these results. First, the change in the interaction intensity (coupling degree) between carbon emissions and the eco-environment does not have a strong influence in the short term but maybe more important in the long-term or have an indirect effect. However, the coordination level (comprehensive evaluation value) has become a decisive factor affecting the coordinated development of carbon emissions and the eco-environment on the mechanistic level. Second, the role of the carbon emission evaluation value in influencing the degree of coordination is stable, especially in specific regions. Although the eco-environment evaluation value produces different effects according to regional differences, it transforms the development trend of coordination degree in most provinces. Yang and Hu (2019) also reported that environmental degradation will restrict the coordinated development of the society, which implies that China's efforts to reduce carbon emissions and protect the environment are inadequate.

3.4 Coordinated trend of carbon emissions and the eco-environment under different scenarios

The results of this study show that in most provinces of China, the increase in the carbon emission evaluation value was the main factor promoting the increase of the coordination degree, while in some provinces, the eco-environment evaluation value had an inhibiting effect. However, the above observations are based on a scenario that assumes equal importance of carbon emissions and the eco-environment. As shown in Figure 4 (b), due to the different stages of economic development and the geographical environment, the evaluation values of carbon emissions and the eco-environment differ between regions. Although both factors are equally important in social development, the actual contribution of each of the two is unlikely to be equal, especially across large geographical areas (Song et al., 2018). Therefore, it is necessary to consider that regional differences may influence policy priorities (Chen et al., 2016). It can be seen from equation 4 that the contribution coefficients α and β, as subjective regulatory variables, jointly determine the coordination trend of carbon emissions and the eco-environment. The contribution coefficients α and β can be set to account for the priorities of government decision-makers. The advantage of the government lies in the fact that it can adjust technological change and social behavior through institutional policies, e.g., via environmental governance and emission reduction targets, to achieve sustainable development (Glover, 2014; Andrews - Speed, 2016; Choi et al., 2017). This study simulated two scenarios to explore the impact of policy priorities on the degree of coordination. We used data from 2015 to rank the differences between regional carbon emission evaluation value and the eco-environment evaluation value and compared the coordination degree of carbon emissions and the eco-environment under different scenarios.

In figure 7 (a), $\alpha > \beta$ indicates that the government pays more attention to carbon emissions, increasing the carbon emission evaluation value. The results of this scenario show that in provinces where the carbon emission evaluation value was higher than the eco-environment evaluation value, the degree of coordination increased, but when the difference decreased, the increase weakened. However, in provinces where the carbon emission evaluation value was lower than the eco-environment evaluation value, coordination decreased with an increase in the difference. In Figure 7 (b), $\alpha < \beta$ implies that the government pays more attention to the eco-environment, improving the eco-environment evaluation value. Under this scenario, the coordination of provinces whose carbon emission evaluation value was higher than the eco-environment evaluation value somewhat decreased, but with a reduction in differences, the decrease abated. In the provinces where the carbon emission evaluation value was lower than the eco-environment evaluation value, the coordination degree showed an upward trend. If the differences increased, coordination further increased. Both cases suggest that the priorities of government policymakers have a substantial impact on the coordinated development of carbon emissions and the eco-environment. However, this effect will gradually decrease as the difference between the carbon emission and eco-environment evaluation values decreases.

[Insert Fig. 7 here.]

The subjectivity in defining the contribution coefficients, α and β, may lead to inaccurate evaluations of the coupling between carbon emissions and the eco-environment, which potentially limits the provision of useful information for government decision-makers (Shen et al., 2018). Analyzing the variation in coordination resulting from parameter adjustments in both subsystems revealed two distinct phenomena that merit further discussion. The first important finding is that the interaction between carbon emissions and the eco-environment depends on the regional development stage and natural environmental conditions. The spatial distribution of the two evaluation values shown in Figure 4 also confirms this inference. The results further show that the difference between regional carbon emissions and the eco-environment evaluation value significantly affects the effect of government priority adjustments. This indicates that an adjustment of policy priorities can effectively improve the coordination of carbon emissions and the eco-environment in the short term in regions with large differences. In less diverse regions, long-term strategies are more appropriate, to increase both carbon emission and eco-environment evaluation values. The second important finding is that while advocating a green, coordinated, and sustainable development, not only carbon emissions should be controlled but also attention has to be paid to changes in the eco-environment, which conforms to current national conditions. However, as Escobar and Vredenburg (2011) pointed out, sustainable development is largely driven by stakeholders rather than social pressure. The government has always played a leading role in the process of environmental governance in China, and its institutional pressure played a key role in improving environmental performance and achieving sustainability (Dubey et al., 2015, 2017). Although Chen et al. (2016) pointed out that priority changes of policymakers will directly affect regional emission reduction efforts in the short term, the eco-environment and the coordination of carbon emissions and the eco-environment in the process of sustainable development have not been included by local governments. The results of this study can help the government to effectively improve decision-making.

4. Conclusions and policy implications

The pursuit of economic development at the expense of the environment has resulted in destructive growth rates (Zaman and Moemen, 2017). In the context of China’s growing economy, the coordinated development of carbon emission reductions and eco-environmental quality is an important component of building a sustainable economic system. This study adopts the coupling coordination model to examine the coordinated development degree of carbon emissions and the eco-environment in China. The coordination degree was further decomposed by the LMDI method to determine the main influencing factors. Moreover, considering that the government plays a crucial role in carbon emission reduction and environmental protection, the adjustment of model parameters reflected the impact of changes in government priorities on the coordination degree.

The main conclusions are as follows. 1) The coupling between China's carbon emissions and the eco-environment has reached a barely balanced stage, but low coordination will remain the long-term trend in China. Due to regional differences in economic development and environmental quality, the carbon emission and eco-environment evaluation values showed a spatial pattern, so that the coordination degree also differed in different provinces. Although most of the provinces have achieved basic coordination, imbalances in some provinces are still pronounced. 2) The decomposition results show that the coordination level between carbon emissions and the eco-environment is the key to promoting the coordination degree. The interaction intensity has a limited effect in the short term but may have a long-term or indirect effect. Further decomposition indicated that the carbon emission evaluation value positively but differently impacted the coordination of various provinces. On the contrary, the positive effect of the eco-environmental evaluation value was only prominent in some regions, while the restraining effect directly hampered coordination trend in most provinces. 3) Different government priorities, i.e., whether more attention is paid to carbon emissions or the eco-environment, have a significant impact on coordination. However, as the difference between the carbon emission and eco-environment evaluation values gradually shrink, the impact of government policies also decreases. Therefore, the effect of adjusting policy priorities in areas with large internal differences is more pronounced in the short term, while in areas with small differences, policy adjustment is more suitable for long-term strategies.

Three policy implications can be derived from these findings.

First, carbon emission reduction policies should continue to be implemented. A low-carbon economy is essential for promoting sustainable development. Although the carbon emission evaluation value has a certain positive effect, it is not enough to affect the coordination degree. It also reflects the need to further strengthen existing policies to reduce carbon emissions. A possibility would be to reduce the dependence of economic development on energy consumption by continuing to optimize energy consumption structures and energy efficiency. At the same time, it is also essential to actively develop clean energy technologies, improve policies on government subsidies, and strengthen the research on and development of innovative technologies.

Second, environmental protection should be a priority. The eco-environment evaluation value has played a restraining role in balancing emissions and environmental quality in most provinces, and the main factors influencing the eco-environment are vegetated land and carbon sequestration by the vegetation. Therefore, the balance between economic development, population growth, and vegetation coverage should be coordinated. Increased attention should be paid to the impact of land-use change on carbon sequestration in the vegetation. Depending on the situation of the natural environment and social development in a region, policies returning farmland to forestry and grassland should be implemented. There should be a focus on protecting forest resources and implementing ecological compensation mechanisms to minimize or eliminate negative externalities of regional economic growth.

Finally, policy priorities should be appropriately adjusted, and the proportion of renewable energy sources should be increased. The natural environment of the region should be fully considered within the current context of regional development. The main focus of policies should be appropriately adjusted to introduce suitable policies that integrate eco-environmental resources into regional carbon cycles. Where conditions are favorable, the proportion of renewable energy sources should be increased. For example, Sichuan, Yunnan, and Guizhou should increase the proportion of hydropower generation due to their abundant water resources. Sinkiang and Inner Mongolia are examples of provinces with a high potential for investment in wind and solar energy. Coastal areas can increase the utilization of marine energy. Gradually replacing fossil-fuel-based energy with renewable sources not only helps to ensure the energy supply for economic development but also can reduce emissions and help to reduce pressure on the eco-environment.

Acknowledgments

This study was supported by The Major Program of National Social Science Foundation of China (Grant No. 20ZDA084); The Key Program of National Natural Science Foundation of China (Grant No.71934001); The National Natural Science Foundation of China (Grant Nos. 71934001, 71471001, 41771568, 71533004); the National Key Research and Development Program of China (Grant No. 2016YFA0602500); the Strategic Priority Research Program of Chinese Academy of Sciences (Grant No. XDA23070400); Sichuan Province Social Science High-Level Research Team Building.

Appendix A

Weight of each indicator in the carbon emission and eco-environment subsystems, based on data from 2009 to 2015.

Indicators	2009	2010	2011	2012	2013	2014	2015
Economy scale	0.0978	0.0962	0.0964	0.0954	0.0926	0.0920	0.0931
Carbon intensity	0.0267	0.0217	0.0157	0.0179	0.0172	0.0178	0.0185
Per capita GDP	0.0914	0.0877	0.0883	0.0877	0.0861	0.0877	0.0921
Industrial economic structure	0.0201	0.0199	0.0197	0.0198	0.0199	0.0197	0.0201
Population scale	0.0756	0.0749	0.0761	0.0762	0.0743	0.0736	0.0743
Carbon emissions per capita	0.0165	0.0173	0.0188	0.0177	0.0219	0.0211	0.0204
Population distribution	0.0756	0.0749	0.0761	0.0762	0.0743	0.0736	0.0743
Urbanization rate	0.0640	0.0814	0.0782	0.0752	0.0738	0.0782	0.0816
Energy consumption scale	0.0256	0.0263	0.0270	0.0263	0.0299	0.0286	0.0270
Energy intensity	0.0276	0.0291	0.0280	0.0315	0.0309	0.0322	0.0274
Energy consumption distribution	0.0256	0.0263	0.0270	0.0263	0.0299	0.0286	0.0270
Energy consumption per capita	0.0284	0.0264	0.0274	0.0278	0.0368	0.0380	0.0314
Land use area	0.0773	0.0769	0.0787	0.0790	0.0771	0.0765	0.0774
Land economic density	0.1893	0.1834	0.1812	0.1799	0.1749	0.1736	0.1752
Proportion of land use	0.0980	0.0980	0.1003	0.1011	0.0990	0.0977	0.0983
Land use area per capita	0.0603	0.0595	0.0611	0.0620	0.0614	0.0610	0.0621
Net primary productivity	0.0981	0.0905	0.0978	0.0913	0.0969	0.0938	0.0924
NPP distribution	0.0942	0.0857	0.0938	0.0868	0.0928	0.0895	0.0881
NPP strength	0.0535	0.0573	0.0547	0.0493	0.0519	0.0473	0.0472
Area of vegetated land	0.1193	0.1220	0.1182	0.1228	0.1205	0.1185	0.1187
Area of vegetated land per capita	0.2830	0.2882	0.2784	0.2887	0.2826	0.2774	0.2774
Proportion of vegetated land	0.0330	0.0332	0.0318	0.0332	0.0325	0.0319	0.0322
Forest cover	0.1051	0.1075	0.1041	0.1081	0.1060	0.1042	0.1043
Forest area per capita	0.1149	0.1177	0.1140	0.1186	0.1165	0.1147	0.1151
Proportion of forest area	0.0571	0.0583	0.0565	0.0586	0.0575	0.0566	0.0567
Proportion of environmental protection expenditure	0.0419	0.0395	0.0506	0.0425	0.0428	0.0662	0.0679

Note: The result retains four decimal places.

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Table caption

Table 1: Index evaluation system of carbon emissions and the eco-environment in China

Table 1 Index evaluation system of carbon emissions and the eco-environment in China

System	Areas	Indicators	Indicator description	Type
Carbon emission	Economy	Economy scale	Real gross regional product (Yuan)	+
		Carbon intensity	Carbon emissions per unit of GDP (t/ Yuan)	-
		Per capita GDP	GDP/Population (Yuan/person)	+
		Industrial economic structure	Proportion of industrial added value in GDP (%)	+
	Population	Population scale	Population at Year-end by region (Per person)	+
		Carbon emissions per capita	Carbon emissions/Population (t/ person)	-
		Population distribution	Proportion of regional population in the total population (%)	+
		Urbanization rate	Proportion of urban population at Year-end by region (%)	+
	Energy	Energy consumption scale	Total energy consumption (Coal, Oil and Natural gas) (T)	-
		Energy intensity	Energy consumption per unit of GDP (T/ Yuan)	-
		Energy consumption distribution	Proportion of regional energy consumption in total consumption (%)	-
		Energy consumption per capita	Energy consumption / Population (t/person)	-
	Anthropogenic land use	Land use area	Total amount of land used for industrial and mining, transportation, water conservancy and agricultural facilities in urban and rural areas (ha)	+
		Land economic density	Land use area per unit of GDP (Yuan/ha)	+
		Proportion of land use	Proportion of land use area in land area (%)	+
		Land use area per capita	Land use area/ population (ha/person)	+
Eco-environment	NPP	Net primary productivity	Carbon sequestration capacity of vegetation (t)	+
		NPP distribution	Proportion of regional NPP in the total NPP (%)	+
		NPP strength	NPP per unit land coverage(t/ha)	+
	Natural land cover	Area of vegetated land	Total amount of cultivated land, gardens, woodlands, meadows, and marshes (ha)	+
		Area of vegetated land per capita	Vegetated land / population (ha)	+
		Proportion of vegetated land	Proportion of vegetated land in relation to total land area (%)	+
	Forest cover	Forest cover	Forest resources by region (ha)	+
		Forest area per capita	Forest area / population (ha)	+
		Proportion of forest area	Proportion of forested area to total land area (%)	+
	Government environmental expenditure	Proportion of environmental protection expenditure	Proportion of expenditure for environment protection to total local financial expenditure (%)	+

Note: + represents positive indicators; - represents negative indicators.

Figures caption

Fig. 1: Trend of Carbon emissions and vegetation carbon sequestration in China from 2009 to 2015

Fig. 2: Distribution of China's carbon emissions and vegetation carbon sequestration in 2009 and 2015

Fig. 3: Coordination degree between China's carbon emissions and the eco-environment from 2009 to 2015

Fig. 4: Distribution of evaluation values for carbon emissions and the eco-environment in China

Fig. 5: Decomposition of the coordination degree of carbon emissions and the eco-environment from the mechanistic perspective

Fig. 6: Decomposition of the coordination degree of carbon emissions and the eco-environment from the composition perspective

Fig. 7: Trend of coupling coordination degrees under different policy priority scenarios

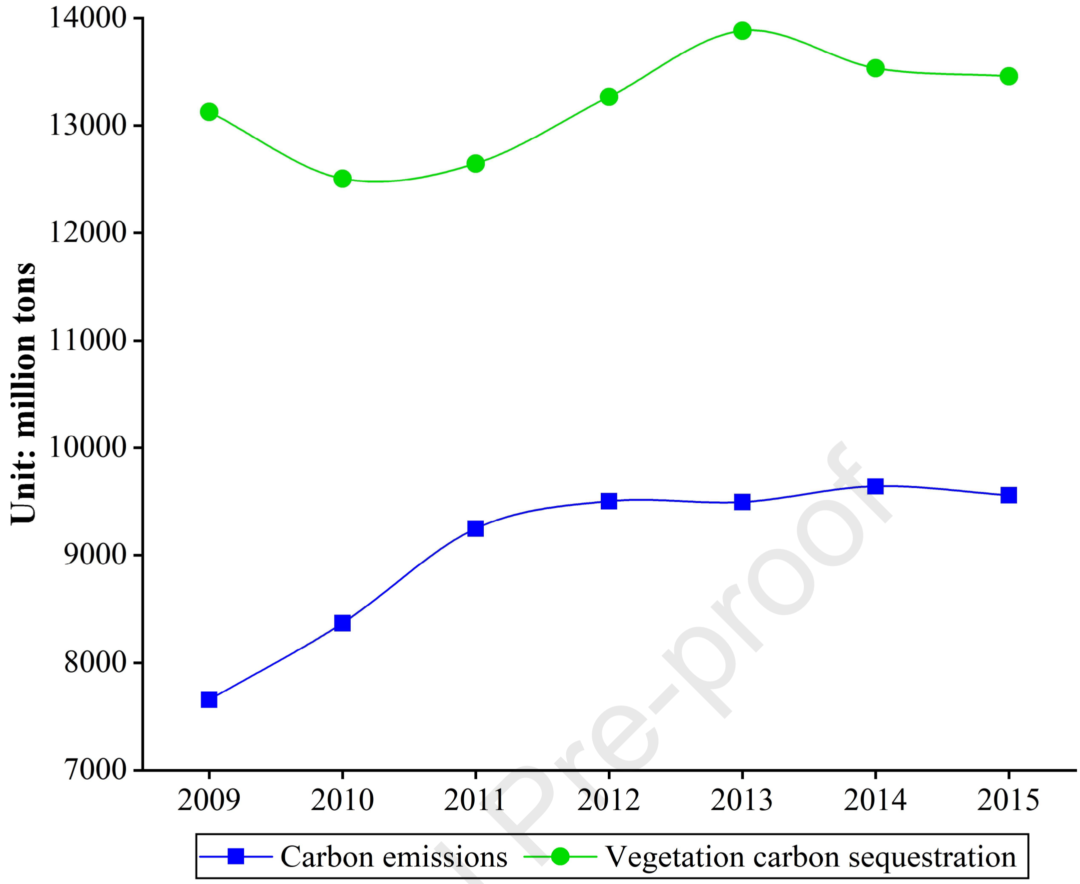

Fig. 1 Trend of Carbon emissions and vegetation carbon sequestration in China from 2009 to 2015

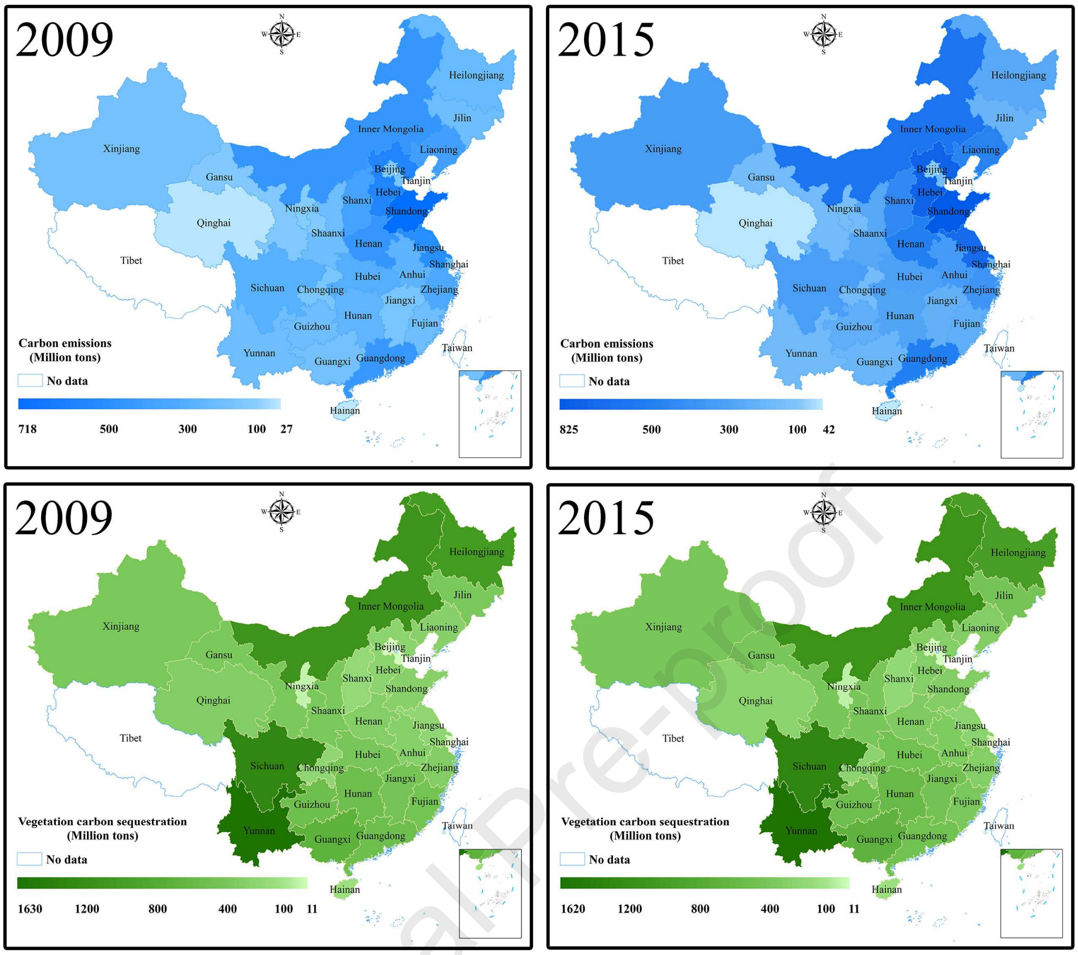

Fig. 2 Distribution of China's carbon emissions and vegetation carbon sequestration in 2009 and 2015

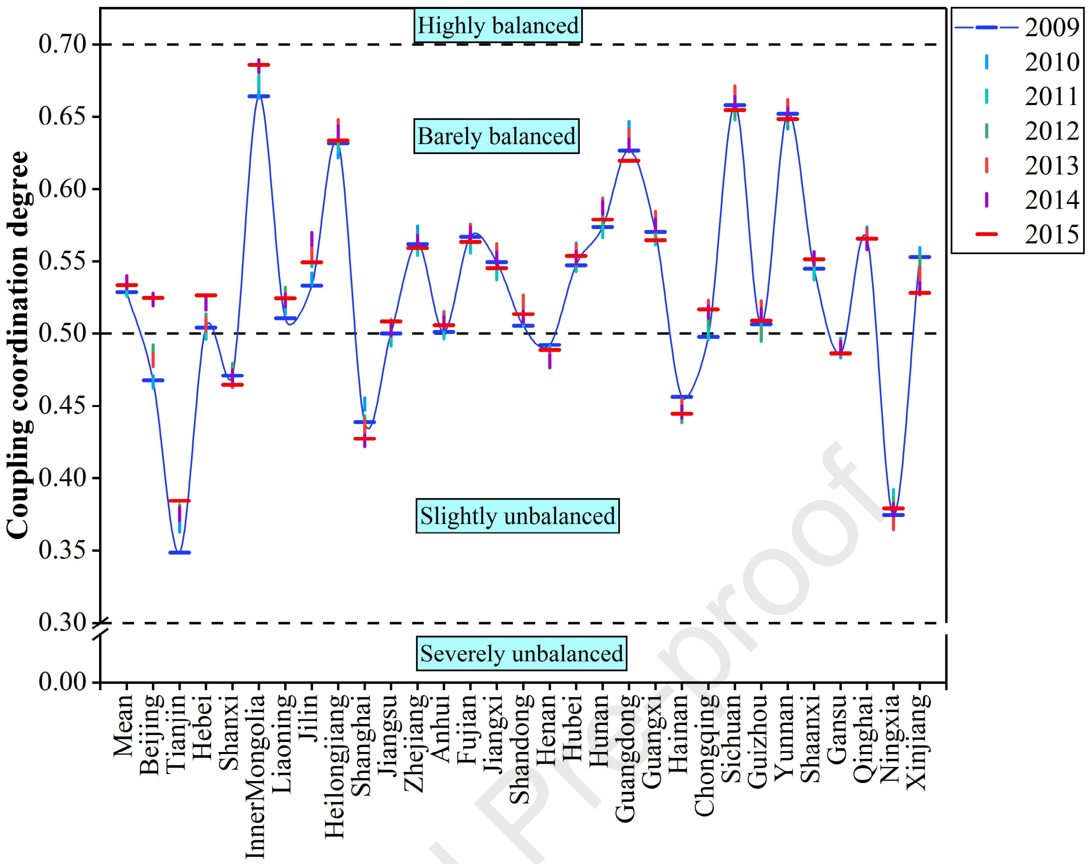

Fig. 3 Coordination degree between China's carbon emissions and the eco-environment from 2009 to 2015

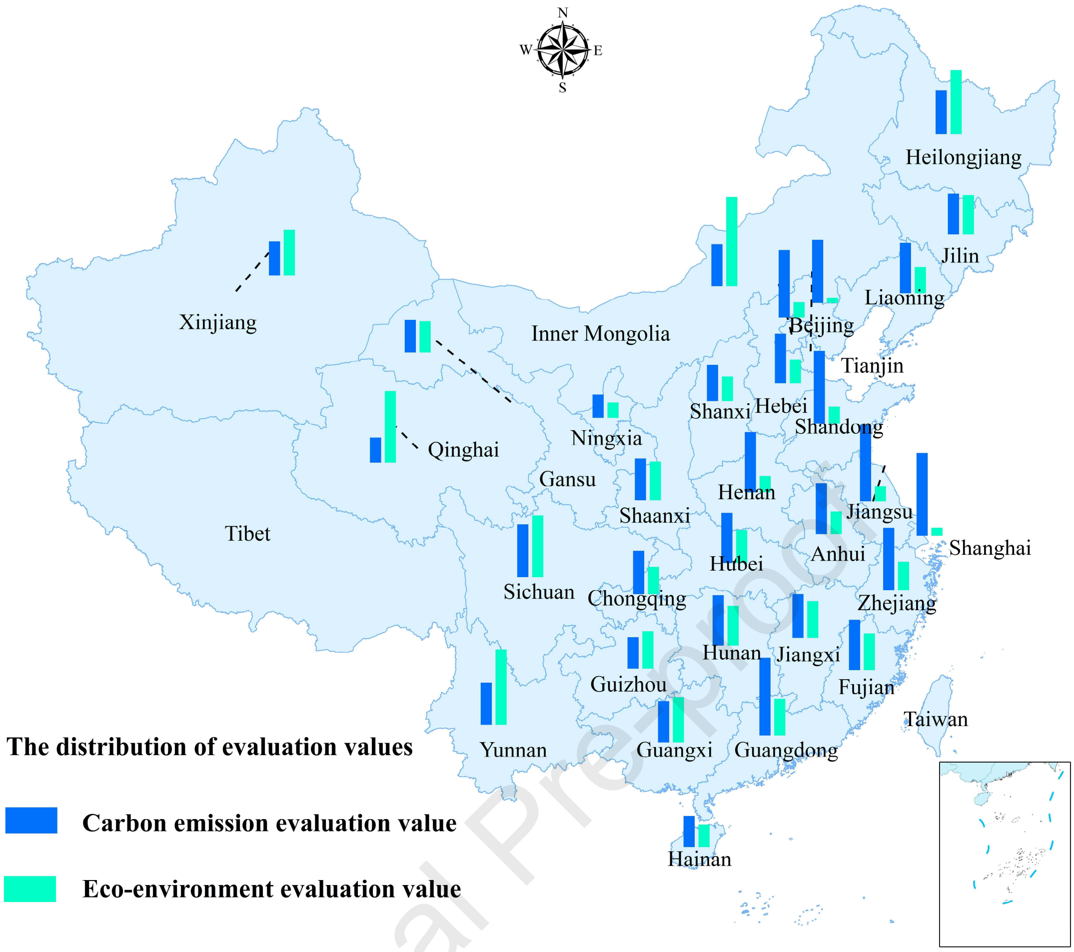

Fig. 4 Distribution of evaluation values for carbon emissions and the eco-environment in China

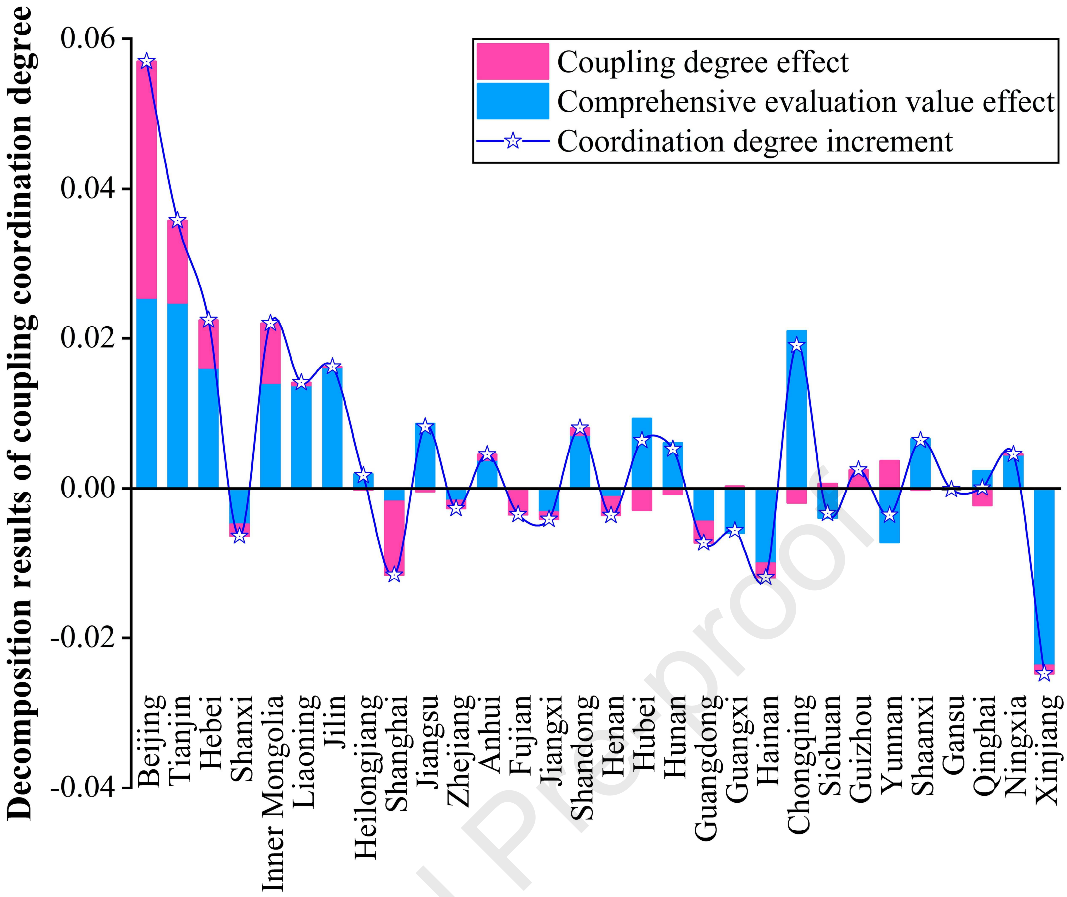

Fig. 5 Decomposition of the coordination degree of carbon emissions and the eco-environment from the mechanistic perspective

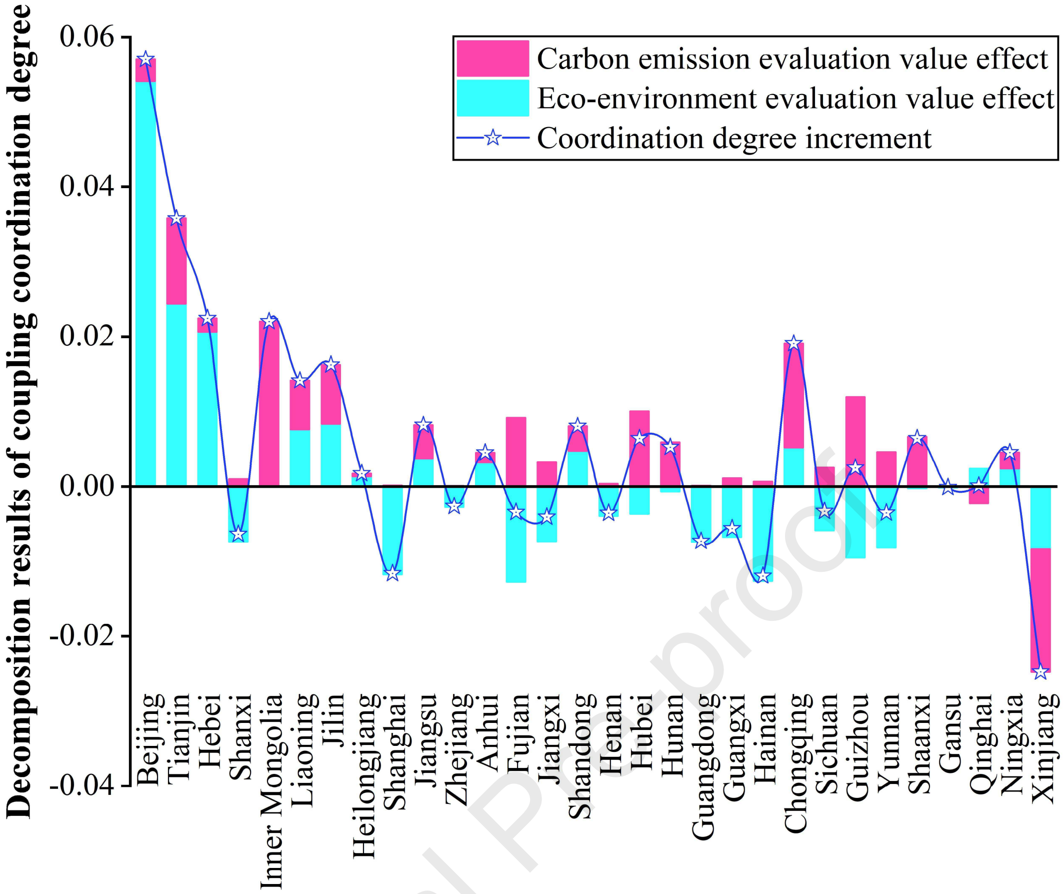

Fig. 6 Decomposition of the coordination degree of carbon emissions and the eco-environment from the composition perspective

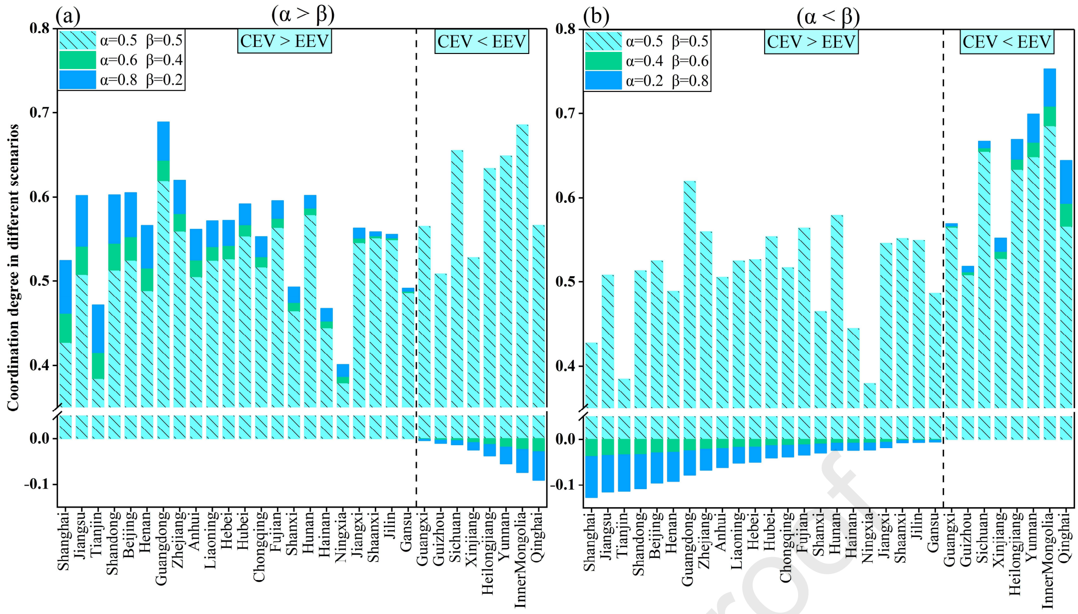

Fig. 7 Trend of coupling coordination degrees under different policy priority scenarios

Conflict Of Interest Statement

All authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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